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Submovements Grow Larger, Fewer, and More Blended During Stroke Recovery

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Submovements are hypothesized building blocks of human movement, discrete ballistic movements of which more complex movements are composed. Using a novel algorithm, submovements were extracted from the point-to-point movements of 41 persons recovering from stroke. Analysis of the extracted submovements showed that, over the course of therapy, patients' submovements tended to increase in peak speed and duration. The number of submovements employed to produce a given movement decreased. The time between the peaks of adjacent submovements decreased for inpatients (those less than 1 month post-stroke), but not for outpatients (those greater than 12 months post-stroke) as a group. Submovements became more overlapped for all patients, but more markedly for inpatients. The strength and consistency with which it quantified patients' recovery indicates that analysis of submovement overlap might be a useful tool for measuring learning or other changes in motor behavior in future human movement studies.

Key Words: movement smoothness, scattershot algorithm, robotic therapy, ballistic movement

During a kinematic analysis of stroke recovery, Krebs et al. (1999) observed a striking feature of the earliest movements made by recovering patients—they were "fragmented" and each of the fragments was highly stereotyped. This provided evidence that normal movement is composed of submovements which are minimally damaged by stroke. The fragments appeared to blend together as recovery proceeded,

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thereby making movement smoother. In subsequent work (Rohrer et al., 2002), we showed that movement smoothness increased measurably and significantly and in a manner fully consistent with a theory of submovements, and did so in patients with a wide variety of ages, impairment severities, and time post-stroke. The nature of those changes supported a theory that patients' movements were comprised of discrete submovements that grew more blended during recovery. In this article we further explore the use of discrete submovements as measures of recovery.

The existence of submovements has been supported by a wide range of studies over the past 100 years. These include observations of slow movements (Vallbo & Wessberg, 1993), eye saccades (Collewijn et al., 1988), cyclical movements (Woodworth,1899; Crossman & Goodeve, 1983; Doeringer, 1999), ballistic movements (Morasso, 1981), and movements requiring high accuracy (Milner, 1992). Especially relevant to our work on stroke recovery is the observation that movements made by developing infants initially exhibit isolated submovements which subsequently appear to blend together as motor skills develop (von Hofsten,1991), a process that could be strikingly similar to our observations of recovery following injury to the central nervous system.

The proposal that unimpaired continuous movement is composed of blended submovements is theoretically attractive, in part because of its similarity to the hierarchical structure of language. Submovements provide a compact language for concisely coding movement; they can be described as fundamental building blocks of which movements are comprised, similar to words in a sentence or phonemes in a word. In the context of stroke recovery, the arrangement and characteristics of the building blocks might change during therapy, but the nature of the blocks themselves appears to remain constant. In this work, we investigate the nature of submovement changes during recovery. Submovement characteristics could provide new quantitative measures of motor performance, as well as provide insight into the nature of neural mechanisms underlying adaptation and motor recovery.

Methods

Participants

Forty-one participants, 12 women and 29 men, participated in this study conducted at the Spaulding Rehabilitation Hospital in Boston, MA. Fifteen participants were acute-stage inpatients who had suffered their first unilateral infarct less than 1 month before beginning the study, and 26 were chronic-stage outpatients between 12 to 54 months post-stroke. Participants ranged between 19 and 83 years of age (mean age 59.0 years for inpatients, 54.4 years for outpatients). They were all hemiparetic, but were able to understand and carry out verbal instructions. Participants' Fugl-Meyer scores for upper-extremity function ranged between 3 and 54 (mean 11.9 for inpatients, 29.8 for outpatients). The protocol was approved by the Human Studies Committee at Spaulding Rehabilitation Hospital and by the Committee on the Use of Human Experimental Subjects of the Massachusetts Institute of Technology. All participants gave informed consent.

Apparatus

MIT-MANUS and InMotion2 were the robotic therapy aids employed in this study. MIT-MANUS was designed and fabricated in the Newman Laboratory at the Massachusetts Institute of Technology (Hogan et al., 1995; Krebs et al., 1998, 1999), and InMotion2 was based on its design and fabricated by Interactive Motion Technologies, Inc., Cambridge, MA. Both are planar robots, freely allowing all motion within a horizontal plane. A key characteristic of both robots is their "backdrivability," that is, the ability to "get out of the way" when pushed by a participant. Thus, participants' movements were minimally obscured by the dynamics of the robots. During all movements analyzed in this article, the robots were unpowered and acted as passive measurement devices that restricted patients' hand motion to a horizontal plane.

Procedure

Over the course of a therapy session, participants were directed to make a number of point-to-point movements, ending as near to the directed point as possible. When presented with a computer display of a center target, eight targets equally spaced around a circle, and the current position of the robot endpoint, participants moved from the center to each target, and back, starting at "north" and proceeding clockwise. Each target was 14 cm from the center. Inpatient participants typically received robot therapy five times per week, for 4 weeks; outpatients three times per week, for 6 weeks. Each session lasted approximately 1 hr. A computer recorded the position, velocity, and force exerted at the robot handle. In addition, each participant was clinically assessed at the beginning, middle, and end of therapy using several clinical scales administered by a clinician blinded to the type of robotic therapy provided. In the interest of clear presentation, only the Fugl-Meyer Test of Upper Extremity Function (Fugl-Meyer et al., 1975) has been included here. Other aspects of the clinical data have been discussed previously. (Fasoli et al., 2003)

Submovement Extraction Algorithm

The goal of submovement extraction is to infer the submovement composition of a movement from kinematic data. The approach taken here used tangential velocity curves. In the tangential velocity domain, a submovement is represented as a unimodal, bell-shaped function. Determining the number, relative timing, and amplitude of submovements that most closely reproduce the original tangential velocity data is a global nonlinear optimization problem, which problems are, in general, difficult to solve. Although several submovement extraction algorithms have been proposed previously (Morasso & Mussa-Ivaldi, 1982; Flash & Henis, 1991; Milner, 1992; Berthier, 1996; Lee et al., 1997; Burdet & Milner, 1998), all are subject to finding local, rather than the global, minima and producing spurious decomposition results (Rohrer & Hogan, 2003). Principal Components Analysis was also evaluated for use in submovement extraction but was found to be inappropriate in that it extracted continuous time components spanning the entire movement, containing parts of several submovements. An algorithm guaranteed to find the global minimum in extraction was proposed in Rohrer & Hogan (2003). As a result of the computational demands of that approach, for the work presented here we developed an alternative submovement extraction algorithm, based on the notion of "scattershot" optimization, that is, local optimization starting from a number of random initial conditions. The scattershot algorithm finds the globally optimal submovement composition probabilistically, that is, the probability of finding the globally best fit can be made arbitrarily close to one by increasing the number of random starting points used in the optimization.

Submovements were extracted from participants' tangential velocity data using MATLAB's fmincon function (MATLAB®, The MathWorks, Natick, MA) initialized at 10 randomly selected points in the solution space. The submovement functions extracted were support-bounded lognormal (LGNB) curves, a submovement shape proposed by Plamondon (1992) and found to fit point-to-point drawing movements better than 22 other candidate functions (Plamondon et al., 1993). LGNB submovements can take on a wide range of submovement-like shapes. Submovement start time, maximum speed, and duration can all be varied independently, as can the skewness (asymmetry) and kurtosis ("fatness") of the curve. Submovements were allowed to take on a duration between 167 ms and 1500 ms. Submovements were not fit one at a time, as in a "greedy" algorithm. Rather, all the parameters of all the submovements were optimized simultaneously. An increasing number of submovements were fit to each movement until the error, E, fell below a predetermined threshold, in this case 2%. Absolute error was used, that is, for a movement speed profile, *G(t)*, and an extracted speed profile, *F(t)*, the error, E, is given by

$$E = \frac{\int |F(t) - G(t)| dt}{\int |G(t)| dt}$$

Five characteristics of the submovements are summarized in the results plots. Each submovement is characterized individually by its duration and peak speed. The relative and collective characteristics of the submovements are represented by the number of submovements in the entire movement, inter-peak interval (interval between peaks of consecutive submovements), and overlap (interval between initiation of a submovement and termination of the previous one).

The scattershot algorithm is probabilistic in nature, that is, the results are globally optimal with some probability close, but not equal to, unity. As a result, the actual submovement characteristics extracted for a given submovement might not be optimal—that is, the submovements extracted cannot be guaranteed to be the best fit for that movement in a global sense. The large amount of data and large number of participants involved in the study, however, allows strong statistical statements to be made from the data. Even if the results of any given extraction could be uncertain, the trends observed in thousands of extractions bear statistical weight and, in fact, reach significance.

The scattershot algorithm is, of course, sensitive to the parameters under which it operates. The submovement function used (e.g. LGNB, minimum jerk, Gaussian), the maximum allowable submovement duration, and the maximum permissible fit error all were shown to produce slightly different results. A sensitivity analysis was performed to determine the dependence of results on these factors. Although too lengthy to be reported here in full, it can be found in Rohrer (2002). It was concluded that the *changes* in extracted submovement parameters during therapy are robust to all these factors. Therefore, changes in submovement parameters will be emphasized in the Results and the Discussion sections.

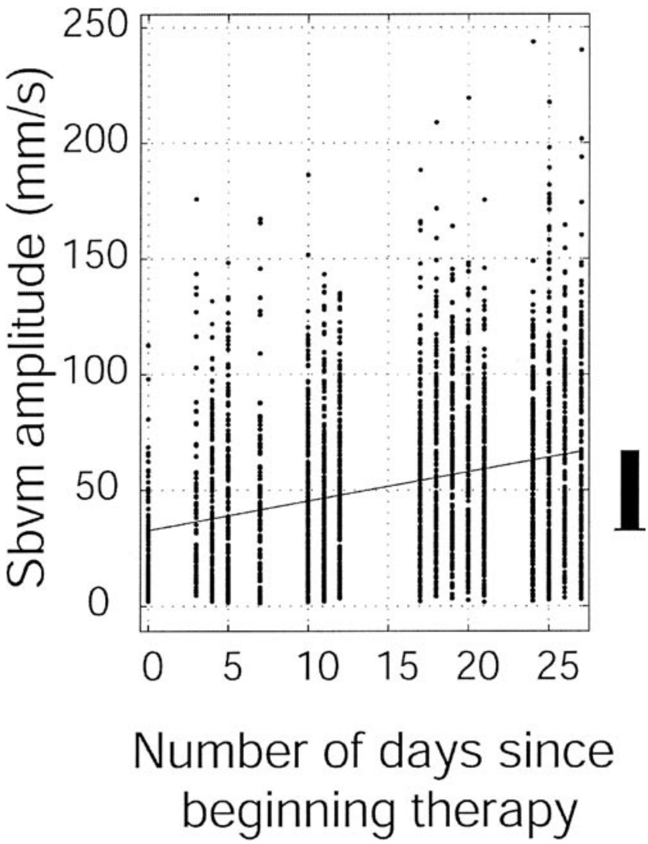

Figure 1 Creation of a "change bar" used in the results summary plots. Each point represents a single submovement. A line was fit to the data using least-squares regression. The bar to the right of the plot represents the change in the parameter value over the course of therapy, with the horizontal line on the bottom indicating the value of the parameter at the beginning of therapy and the height box indicating the extent of the change during therapy. In subsequent plots, a solid bar represents a statistically significant change (*p* < .05); an unfilled bar represents a change that did not reach statistical significance.

Statistical Analysis

Using linear regression, a line was fit to each of the submovement characteristics over the course of therapy for each participant, and the confidence interval for the slope was determined. See Press et al., (1992) for a detailed mathematical description of the procedure. The change bars in the results summary plots were generated by taking the values of the linear fit at the first and last days of therapy as the initial and final values of the characteristic (Figure 1).

Results

Patients' Submovement Characteristics

Figure 2 shows typical submovements from the first and last therapy days for one participant. Observed differences are representative of the participant population as a whole. Submovements on the last day of therapy are fewer and of greater amplitude and duration than on the first. The final day's submovements also show more extensive overlap. Figure 3 shows the changes in the patients' submovement characteristics over the course of therapy. Figure 4 summarizes the trends in each metric for the patient population as a whole and for inpatient and outpatient groups separately. Despite wide variations between patients, several general observations can be made: (a) every significant change in the number of submovements was a decrease; (b) the participants' submovements tended to increase in duration and peak speed; (c) the inter-peak interval decreased for inpatients, but showed no trend for outpatients; and (d) the only significant changes in submovement overlap were increases.

Figure 2 Typical movements from the first and last days of therapy for participant 701. Bold lines indicate the tangential velocity during the movement. Fine lines indicate the submovements of which the movement is composed. The later movement shows fewer submovements, which have greater peak speed, duration, and overlap than the earlier movement. These differences are representative of those observed throughout the participant population.

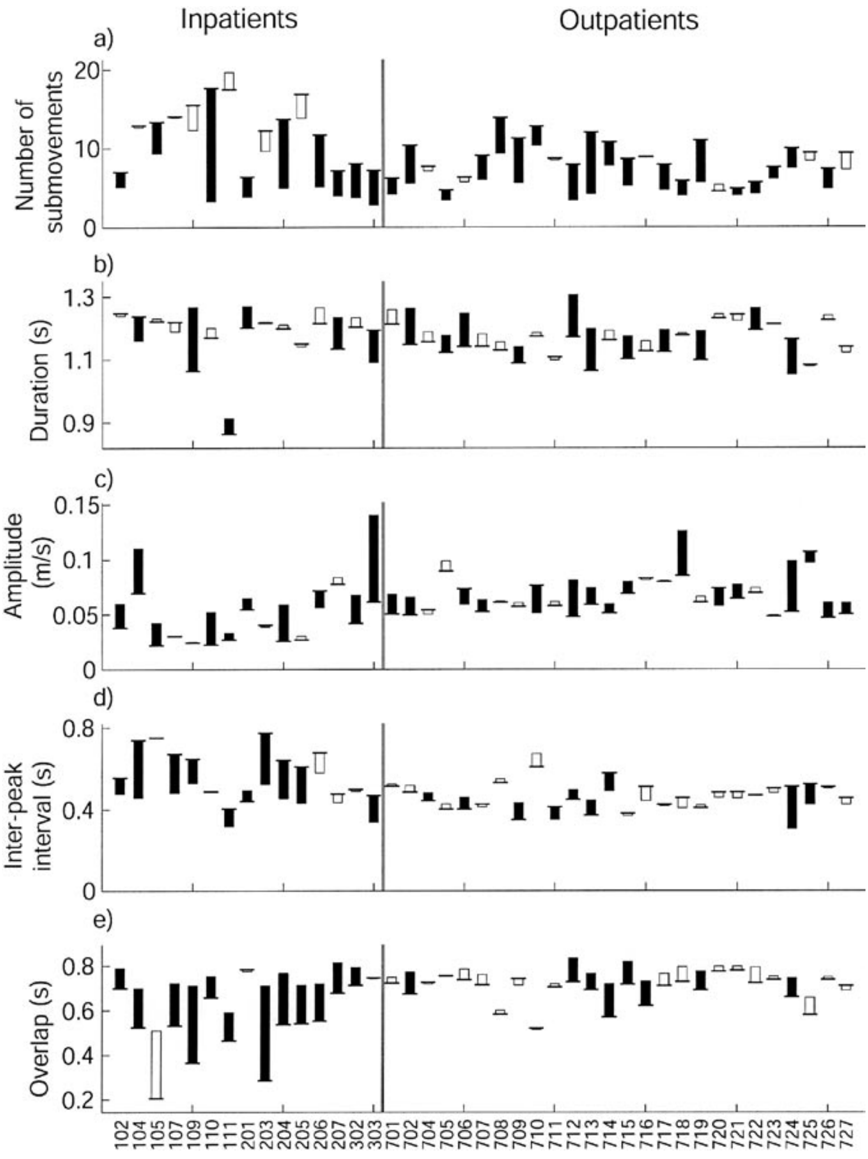

Figure 3 Changes in submovement characteristics by patient. Changes in submovement characteristics from the first day to the last day of therapy are shown for all patients. The initial value is represented by the horizontal bar. For statistically significant changes (p < .05) the box is filled, otherwise it is unfilled.

Several submovement characteristics were comparable for both inpatients and outpatients. Typical submovement durations for both groups were approximately 1200 ms, significantly longer than the 500 ms typically observed. (See the Discussion section for further details.) Eight submovements per movement was typical for both groups, as well, and on average, submovement amplitudes were near .07 m/s.

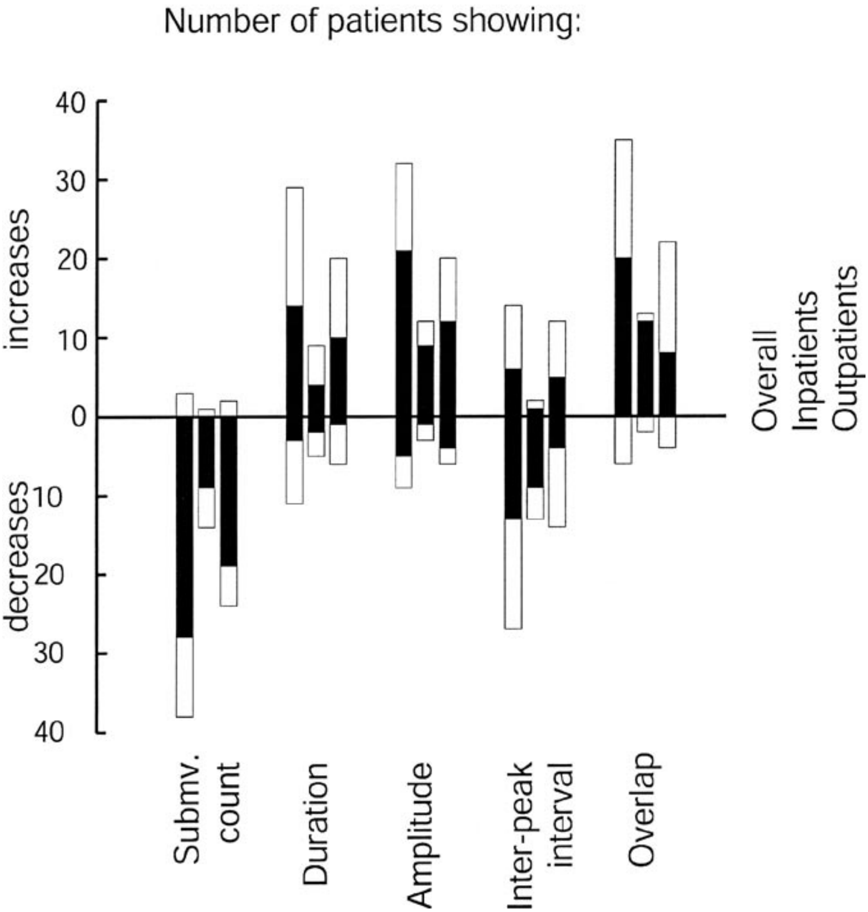

Figure 4 The number of patients who showed increases and decreases in each of five submovement characteristics, by inpatient group, outpatient group, and overall. White bars indicate the total number of participants in each group showing a change, and black bars indicate how many of those were statistically significant at the *p* < .05 level.

For inter-peak interval and submovement overlap, the magnitude of the changes of inpatients' submovement characteristics were greater than those of outpatients (significant at $p < .05$). With respect to these two characteristics, the final values for outpatients appear to be closely grouped around a common mean. Inpatients' values appear to converge to these common means during therapy. For example, in Figure 3, panel (e), outpatients' values for overlap are all grouped tightly around .7 to .8 s. Inpatients' initial values tend to be lower than .7 s, but (with a few exceptions) increase markedly. The final values of overlap are much more closely grouped around .7 s.

It is to be expected that the inter-peak interval would have a lower bound; not only is it bounded below by zero (by definition), but evidence of a psychological refractory period (Telford, 1931; Craik, 1947) suggests that the lower bound could be significantly higher (Miall et al., 1993). The data presented here shows evidence of inter-peak intervals descending to an asymptote. Although inpatients began with a wide range of inter-peak intervals (from .4 s to .8 s), at the completion of therapy they all fell in a narrow band centered approximately at .45 s. Outpatients tend to begin and end therapy in that same band, the majority of them showing no significant change.

Clinical Measures of Recovery

Inpatients and outpatients had a wide range of Fugl-Meyer scores both at the beginning and end of therapy. On average, however, admission Fugl-Meyer scores were significantly lower in inpatients, as compared to outpatients ($p < .001$). Over the course of robotic therapy, both inpatients and outpatients showed statistically significant gains in Fugl-Meyer scores ($p < .0001$).

Although the patients' age range was quite large, there was no statistically significant difference in age between inpatients and outpatients as groups. Therefore, the observed differences in inpatient and outpatient performance cannot be attributed to variations in patients' ages. Furthermore, changes in patients' submovement characteristics showed no meaningful correlation with age, yielding r^2 < .07 in all cases (see Table 1).

Table 1 Single-variable correlation between changes in each submovement characteristic and changes in the Fugl-Meyer, time post-stroke, and participant's age (square of Pearson's *r*).

Submovement characteristic	Number	Duration	Amplitude	Inter-peak interval	Overlap
Age	.06	.00	.00	.03	.04
Change in Fugl-Meyer	.01	.00	.08	.04	.05
Time post-stroke	.07	.00	.07	.19	.29

To test how accurately observations of submovement characteristics were predicted in clinical scores, single-variable correlations were calculated between changes in each of the five submovement characteristics, changes in the Fugl Meyer score and time post-stroke (see Table 1). For $N = 41$ participants at a 5% significance level, correlations become significant at $r^2 > .0949$ (Press et al., 1992). The correlation is statistically significant in only two cases; inter-peak interval and overlap correlated with time post-stroke ($r^2 = .19$ and $r^2 = .29$, respectively). This indicates that changes in submovement characteristics are not directly related to changes in Fugl-Meyer scores, but could be somewhat related to time post-stroke.

Discussion

In previous work, we demonstrated that movement smoothness tends to increase during stroke recovery, and that the increases in smoothness are well described by a model of changes in submovement characteristics (Rohrer et al., 2002). Here, by directly extracting submovements, we provide additional support for a model of discrete submovements and find greater insight into the nature of motor recovery after a stroke.

Submovement Characteristics

Significant changes were observed in the submovement characteristics of both inpatients and outpatients. Submovement durations and amplitudes increased, inter-peak interval and overlap decreased, and the total number of submovements grew fewer. Despite uncertainties in the precise values of the extracted submovement characteristics, it is nonetheless interesting to consider the values produced. For instance, an inter-peak interval of .4 to .5 s indicates that new submovements are being initiated on average 2 to 3 times each second. This is quite plausible; prior work involving human performance during pursuit tracking tasks showed that participants made discrete corrections on the average of once every one-half second (Craik, 1947).

Extracted submovement durations of 1.2 s are longer than previously observed ballistic movement durations (Beggs & Howarth, 1972). This might be caused by the tendency of LGNB submovements to develop long tails when they become significantly asymmetric. The long tail contributes very little to the movement speed, but does result in an artificially long submovement duration. A more physically meaningful measure of submovement duration would be the length of time that the submovement exceeds 5% of its peak speed. This would eliminate the artifacts generated by excessively long tails.

Time Course of Recovery

Inpatients' and outpatients' submovements shared many trends, but they differed in one key aspect: while inpatients' submovements consistently grew closer together (inter-peak interval decreased), outpatients' submovements showed no such trend. Furthermore, inpatients' inter-peak interval seemed to approach a limit, defined by outpatients' typical values. This suggests that during recovery inter-peak interval follows an asymptotic time-course, approaching a minimum value, over a time period on the order of 1 year. Further investigation is necessary to reveal whether other submovement characteristics also follow asymptotic patterns, and on what timescales.

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